Juggling Act: Caregiving for an Elderly Family Member and Female Labor Market Earnings[*]

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The 65-and-over population in 2030 is projected to be twice as large as in 2000, growing from 35 million to 72 million, and representing nearly 20 percent of the total U.S. population (U.S. Census Bureau, 2008). With this projected increase in the number of older people, will come the added demands on families, health care providers, businesses, and policymakers to meet the needs of the aging population. According to the U.S. Department of Health and Human Services, 38 percent of non-institutionalized people 65 and over in the United States have a physical limitation that restricts their ability to perform such tasks as lifting or reaching, and 19 percent have difficulty with one or two activities of daily living such as walking, getting in and out of a bed or chair, or bathing or showering (National Center for Health Statistics, 2005). About 70 to 80 percent of older people receive care from friends and family, sometimes with help from supplementary paid helpers (U.S. Census Bureau, 2005). For working individuals who provide care to an elderly family member, such care often entails leaving work early or going in late, taking an extended leave of absence, or even quitting their job (National Alliance of Caregiving and American Association of Retired Persons, 2004; MetLife, 2001). Several papers, using various data sources and methodologies, have examined the impact of caregiving on labor market outcomes such as labor market participation, hours of work, and earnings (e.g., Johnson and Lo Sasso, 2006; Wakabayashi and Donato, 2005; Pavalko and Artis, 1997; Ettner, 1996, 1995; and Wolf and Soldo, 1994).

In this paper, we examine the impact of work interruptions (periods of not working for six months or longer) due to providing care for an elderly family member on the earnings of females aged 25 to 62 using data from the 2004 panel of the Survey of Income and Program Participation. Employing a human capital framework, we estimate earnings equations accounting for selection into the labor market for two groups: employed females who have had a caregiving interruption at some point during their work careers and employed females who have never had a caregiving interruption during their work careers. Females who have had a work interruption due to providing care for an elderly family member earn on average 75 percent of that of females who have never had a work interruption due to providing care for an elderly family member. The observed earnings differential between these two groups is evaluated using the Blinder-Oaxaca decomposition technique to identify the share of the observed earnings differential that is explained by human capital differences and the share attributed to labor market imperfections.

JEL Codes: J31, J24, J14

Presentation: Southern Economic Association Annual Meetings
Washington, DC
November 20-23, 2008

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[*] This paper reports the results of research and analysis undertaken by U.S. Census Bureau staff. It has undergone a more limited review than official U.S. Census Bureau publications. This paper is released to inform interested parties of research and to encourage discussion.

I. INTRODUCTION

According to U.S. Census Bureau projections, a substantial increase in the number of older people will occur during the 2010 to 2030 period, after the first Baby Boomers turn 65 in 2011 (U.S. Census Bureau, 2008). The 65-and-over population in 2030 is projected to be twice as large as in 2000, growing from 35 million to 72 million, and representing nearly 20 percent of the total U.S. population by the latter date (U.S. Census Bureau, 2008). With this projected increase in the number of older people, will come the added demands on families, health care providers, businesses, and policymakers to meet the needs of the aging population.

According to the U.S. Department of Health and Human Services, 38 percent of non-institutionalized people 65 and over in the United States have a physical limitation that restricts their ability to perform such tasks as stooping, lifting, reaching, grasping, or walking, and 19 percent have difficulty with one or two activities of daily living such as walking, getting in and out of a bed or chair, or bathing or showering (National Center for Health Statistics, 2005). As a result, older people with physical limitations and difficulties in performing daily activities are likely to require assistance in some form or another on a regular basis.

Caring for an elderly family member requires a significant time investment (and potentially significant financial outlay) on the part of the caregiver. To provide the means for meals, personal hygiene, and social interaction required to maintain the well-being of the elderly family member involves the devotion of time and financial resources. Given adequate financial resources and understanding employers, some caregivers are able to take time off from work to provide such care without incurring immediate financial hardship.[1] Other caregivers have to rely on other family members and social networks, in addition to private agencies and government social programs, to provide care, either due to limited financial resources (e.g., they can not afford to take time off from work or reduce their hours worked) or personal family obligations, or both. About 70 to 80 percent of older people receive care from friends and family, often with help from supplementary paid helpers (U.S. Census Bureau, 2005). Over 65 percent of older people depend solely on unpaid help (U.S. Census Bureau, 2005). The majority of informal caregivers are female, with estimates of the percentage of informal caregivers who are women ranging from 59 percent to 75 percent (Family Caregiver Alliance, 2003).[2]

For working individuals who provide care to an elderly family member, such care often entails leaving work early or going in late, taking an extended leave of absence, or even quitting their job (National Alliance of Caregiving and American Association of Retired Persons, 2004; MetLife, 2001). For those caregivers who do interrupt their work careers (i.e., stop working entirely) to provide care for an elderly family member, regardless of financial resource adequacy and employer willingness to allow such time off, do they incur some "penalty" for this work career interruption? Do individuals who have interrupted their work careers to provide care for an elderly family member have lower levels of earnings than those individuals who have never had a work career interruption due to providing care for an older family member?

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[1] Of companies with 100 or more employees, about one-quarter have programs to support elder care (Families and Work Institute, 1997).
[2] For more information concerning U.S. caregiving statistics and characteristics, see Family Caregiver Alliance (2003) and National Alliance of Caregiving and American Association of Retired Persons (2004).

Human capital theory predicts, ceteris paribus, that those with higher levels of labor market experience will have higher levels of labor market earnings (Mincer, 1974). Choosing to take time off from work to provide care for an elderly family member should result in lower earnings because those making this decision are investing less in human capital that is likely to generate a return from the labor market. In addition, as a result of taking time off to provide care for an elderly family member, some caregivers may have to forgo promotions or other advancement opportunities, thereby limiting their future earnings potential.[3] Others may not be able to return to their pre-caregiving employer or career, thereby forcing them to transition to a new employer or field of work, most likely at reduced or entry-level wages.

Several papers, using various data sources and methodologies, have examined the impact of caregiving on labor market outcomes such as labor market participation, hours of work, and earnings. As a result of the varying analysis sub-groups, data sources, and methodologies examined in the literature, the findings as to the impact of caregiving on labor market outcomes are mixed.

Johnson and Lo Sasso (2006) use data from the Health and Retirement Study to examine the impact of elder care on the labor supply of women aged 55 to 67, and they find that providing assistance to parents strongly reduces female labor supply at midlife. According to their estimates, women aged 55 to 67 who provide care to their parents reduce their work hours by almost half.

Drawing data from the National Survey of Families and Households (NSFH), Wakabayashi and Donato (2005) find that for most women, the onset of caregiving led to

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[3] In one national study, 29 percent of employed caregivers have turned down a job promotion, training, or other assignment due to having to provide care (MetLife Mature Market Institute, et al., 1999).

a significant reduction in their weekly hours worked and annual earnings. The effects were different for various subgroups of women, with older women, and those possessing fewer skills and more competing roles, experiencing the larger labor market costs.

Using data from the National Longitudinal Survey of Mature Women, Pavalko and Artis (1997) find that a woman's decision about whether they became a caregiver was not affected by their employment status. However, once a woman started to provide care, they were more likely to reduce their hours worked or to leave the labor force. Furthermore, even when their caregiving duties ended, they did not increase their hours worked, suggesting difficulty with recouping the employment losses associated with their time out of the workforce.

Also using NSFH data, Ettner (1996) finds that providing care to elderly parents who did not co-reside with the caregiver reduced hours of work for women (but not for men) caregivers, and Wolf and Soldo (1994) find that caring for elderly parents or parents-in-law had no significant effect on married women's labor supply.

Lastly, Ettner (1995) uses data from the Survey of Income and Program Participation, and when using instrumental variable techniques, finds that providing more than 10 hours of care per week does not significantly reduce hours worked. When the author did not instrument for care, providing care to a co-residing elderly family member significantly reduced women's hours worked.

To date, we are not aware of any literature directly addressing the impact of caregiving interruptions on the earnings of female caregivers. In this paper, we examine the impact of work interruptions (i.e., periods of not working for six months or longer) due to providing care for an elderly family member on the earnings of females aged 25 to

62 using data from the 2004 panel of the Survey of Income and Program Participation. Employing a human capital framework, we estimate earnings equations accounting for selection into the labor market for two groups: employed females who have had a caregiving interruption at some point during their work careers and employed females who have never had a caregiving interruption during their work careers. The observed earnings differential between these two groups is evaluated using the Blinder-Oaxaca decomposition technique to identify the share of the observed earnings differential that is explained by human capital differences and the share attributed to labor market imperfections, controlling for selectivity.

The remainder of this paper is organized as follows: section two will provide a description of the data used in the analysis; section three will describe the methodology employed; section four will present the results of our analyses; and the final section will provide concluding remarks.

II. DATA

The data we use in this paper are from the 2004 panel of the Survey of Income and Program Participation (SIPP), which is collected, processed, and distributed by the U.S. Census Bureau. The survey's population universe is the civilian non-institutionalized population of the United States. The SIPP collects detailed information on demographics, income, employment, government transfer program participation (e.g., Temporary Assistance for Needy Families (TANF), food stamps, and unemployment insurance), and health insurance coverage. Each household included in the SIPP is selected via a two-stage sample and interviewed every four months, a period called a "wave." Comprising twelve waves, the 2004 SIPP panel was fielded from February 2004 to September 2008.[4] In wave one, approximately 43,700 households were interviewed either in person or by telephone.[5]

The SIPP is comprised of core and topical module data. Core data pertain to the basic items in the SIPP, such as demographics, program participation, income, and employment, while topical module data pertain to special topics such as wealth, marital and fertility history, disability, employment history, and education and training history. The core questions of the SIPP are asked every wave of the survey, while topical module questions are only asked during certain waves and usually for one wave only, though some modules are asked multiple times (e.g., the wealth topical module, which is administered every three waves).

In particular, this paper uses merged core and topical module data. Basic demographic, employment, and earnings data are obtained from the wave one core portion of the survey. The topical module data come from the Employment History topical module conducted in wave one of the 2004 panel, which was collected from February through May 2004. The Employment History topical module collects data on individuals' work histories, such as the number of times out of work for six months or longer (i.e., work interruptions) and the reason(s) for any work interruption(s) due to caregiving, such as caring for a child, elderly family member, or disabled person. The Employment History topical module does not contain retrospective earnings or occupation data.

Lastly, because of the SIPP's complicated survey design, weights are required to conduct analyses and produce consistent estimates. All results presented in this paper are

[4] The 2008 panel of the SIPP began in September 2008 and will be administered through December 2012.
[5] Weighted, the 43,700 unweighted households represent approximately 112 million households.

based on weighted estimates and all standard errors have been adjusted to account for the SIPP's complex survey design (for a complete discussion of the SIPP sample selection, weighting procedures, and standard error adjustment for the 2004 panel, see U.S. Census Bureau, 2007).[6]

III. METHODOLOGY

In order to examine the observed earnings differential between female caregivers and non-caregivers, we jointly estimate the labor market participation decision and log-earnings functions for female caregivers and non-caregivers while accounting for selectivity bias.[7] The outcomes from this simultaneous estimation are used as the basis for our Blinder-Oaxaca decomposition analysis, accounting for selectivity.

It is well recognized in the literature that it is important to account for selectivity bias when analyzing earnings differentials (Greene, 2007; Neuman and Oaxaca, 2003; and Yun, 2000). Even though two-groups are observed to have the same levels of human capital, they may have different levels of unobserved earnings power (e.g., ability and motivation). If female caregivers have more unobserved earning power than non-caregivers due to a different pattern of selection into the labor market, then failing to account for selection will underestimate the "true" differences in rates of return to the same individual characteristics (i.e., the differences in the estimated coefficients of the earnings equation) due to labor market imperfections. Thus, if selection issues are not

[6] All standard errors have been adjusted for the complex sample design of the SIPP by the use of a design effect factor. Specifically, the square root of the design effect factor of 1.80 (i.e., 1.34) was applied to all SAS standard errors. For more information, see U.S. Census Bureau (2007).

[7] Unless otherwise noted and for the remainder of the discussion, we will refer to females who have had a work interruption due to providing care for an elderly family member as "caregivers" and females who have never had a work interruption due to providing care for an elderly family member as "non-caregivers." Also, the term "caregiving" will specifically refer to providing care for an elderly family member.

accounted for, the estimates of labor market imperfections may be biased or misleading. By jointly estimating labor market participation and monthly earnings, we account for the possible existence of selection bias in our data.

Hence, our model is specified as follows:

$$W_{ij} = \beta_{ij}(X_j) + \varepsilon_{ij} \qquad (1)$$

$$P_{ij}^{*} = \alpha_{ij}(Z_j) + \nu_{ij} \qquad (2)$$

where i = (1, … , n) and j = (n for non-caregiver, c for caregiver). W_{ij} is the (natural) logarithm of monthly earnings and P_{ij}^{*} is an underlying variable for labor market participation.[8] Individuals will participate in the labor market (P = 1) when P_{ij}^{*} is positive; they will not participate (P = 0) otherwise.[9] Earnings (W_{ij}) are only observed for those who participate in the labor market and are missing for those who do not participate in the labor market. X_j and Z_j represent exogenous variables, β_{ij} and α_{ij} are the associated parameter vectors, and ε_{ij} and ν_{ij} are error terms. The error terms ε_{ij} and ν_{ij} are jointly normal with zero mean, standard deviations of one and σ, and correlation of ρ. The correlation, ρ, summarizes the selection bias mechanism. Finally, equations (1) and (2) are estimated jointly via maximum likelihood for the non-caregiver and caregiver groups, as well as for the pooled sample (i.e., for our entire female sample).[10]

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[8] Monthly earnings are taken for each individual from month four of wave 1, the month closest to the interview date.

[9] Labor market participation is usually defined to include both employment and unemployment. However, most studies of labor supply do not count unemployment in the definition of participation, thereby treating unemployment as the same as leisure or non-employment. Hence, we treat unemployment as non-participation.

[10] The model expressed in equations (1) and (2) can also be estimated using Heckman's two-step procedure (see Heckman, 1979). However, use of maximum likelihood estimation eliminates the burden of deriving the functional form of the selection bias mechanism. Consequently, maximum likelihood estimation does not introduce a measurement error problem, and is both consistent and efficient (see Kennedy, 2003; Yun, 2000; and Nawata, 1994).

The exogenous variables (X_j) included in equation (1) are: age, dummy variable indicators for race and ethnicity (i.e., whether black or Hispanic), educational attainment (i.e., high-school or equivalent diploma, some college but less than a four-year degree, bachelor's degree, and advanced degree), marital status (i.e., whether currently married), part-time employment (i.e., work less than 35 hours per week), private sector employment, geographic region (i.e., Midwest, West, and South Census regions), occupation (i.e., management and professional, sales and office, and other), and whether an individual had multiple work interruptions (for any reason) over their work career lasting 6 months or longer. The exogenous variables (Z_j) included in equation (2) are the same as in equation (1) minus the dummy variable indicators for part-time employment, private sector employment, occupation, and multiple work interruptions.

We use the estimated coefficients from our joint estimation of equations (1) and (2) for each analysis group (i.e., non-caregivers and caregivers) as input to our decomposition analyses. Following Yun (2000), our decomposition takes the following form:

$$W_n - W_c = \Delta X(\beta_c) + \Delta\beta(X_n) + \Delta\lambda \qquad (3)$$

where W_n and W_c are the mean values for the log monthly earnings for non-caregivers and caregivers, respectively; ΔX represents the difference in sample means of the exogenous variables between non-caregivers and caregivers; $\Delta\beta$ represents the difference in the estimated coefficients from equation (1) between non-caregivers and caregivers; $\Delta\lambda$ represents the difference in the sample average of residuals between non-caregivers and caregivers (i.e., $\varepsilon = W - \beta(X)$); β_c represents the estimated coefficients of equation (1) for caregivers; and X_n represents the means of the exogenous variables of non-caregivers. Our decomposition analysis shown in (3) assumes that the non-caregiver group is the non-discriminatory norm.

As shown in equation (3), the earnings differential between non-caregivers and caregivers can be decomposed into three components: (1) a human capital or endowment component; (2) a labor market imperfections component; and (3) a selectivity component. The first term in equation (3) represents the portion of the earnings differential explained by differences in observed individual characteristics ($\Delta X(\beta_c)$) (i.e., due to differences in human capital and endowments). The second term represents the portion of the earnings differential explained by differences in the coefficients in observed characteristics ($\Delta\beta(X_n)$) (i.e., due to labor market imperfections). Lastly, the third term represents the portion explained by differences in unobserved individual characteristics leading to labor market participation and their resulting returns ($\Delta\lambda$).

IV. RESULTS

Our sample comprises all females 25 to 62 years of age who have worked at some previous time for at least six months or longer. Their characteristics are shown in Table 1. Females currently employed and who have experienced a caregiving interruption over their work career earn on average 25 percent less ($2,112 versus $2,802) than currently employed females who have never had a caregiving work interruption, and females who have experienced a caregiving interruption were more likely to have experienced multiple work interruptions (i.e., two or more, lasting 6 months or longer, and for any reason) over their work career.[11] On average, those females who have had a work interruption due to

[11] The additional time out of the workforce for caregiving may compound the impact of earlier leave taken to care for a child.

caregiving for an older family member were five years older, less likely to be Hispanic, less likely to possess a four-year college or advanced degree, less likely to be married, more likely to live in the southern region of the country, and less likely to be currently employed. Furthermore, those females currently employed and who have experienced a caregiving interruption over their work career were more likely to be part-time workers (i.e., work less than 35 hours per week), and less likely to be employed in a management or professional occupation.[12]

In order to further explore the non-caregiver/caregiver monthly earnings differential shown in Table 1, we first estimate our above described model for the entire female sample by pooling together both non-caregivers and caregivers, and incorporating into our earnings equation a caregiving dummy variable that equals one if an individual had a caregiving interruption and zero otherwise. Then we separately estimate the same regression model for both the non-caregiver and caregiver groups, minus the caregiving dummy variable. As discussed above, the separate sub-group earnings equation regression results provide the basis for decomposing the observed non-caregiver/caregiver earnings differential shown in Table 1.

Table 2 shows the regression results of the earnings and participation equations (i.e., equations (1) and (2) from above) for the pooled sample and the non-caregiver and caregiver sub-groups. Focusing on the earnings equation, we will first discuss the results

[12] One national study found that 33 percent of women who continued to work while providing care decreased their work hours and 20 percent switched from full-time to part-time employment (MetLife Mature Market Institute, et al., 1999). Additionally, Pavalko and Artis (1997) find that women who reduced their work hours while caregiving did not increase their work hours once caregiving ended and Dentinger and Clarkberg (2002) find that caregivers who returned to full-time employment after caregiving were more likely to earn lower wages.

for the pooled sample, followed by a discussion of the sub-group regression results and decomposition analyses.

For the pooled sample (column (1)), of particular note are the multiple interruptions and caregiving dummy variables, which are both significant and negative. The multiple interruptions dummy variable indicates that those experiencing two or more work interruptions (i.e., lasting 6 months or longer and for any reason) over their work career have on average 13 percent lower earnings compared to those who have not had multiple interruptions over their work career.[13] Additionally, and of our primary interest, the dummy variable indicating whether an individual experienced a work interruption for caregiving, indicates that on average those experiencing such an interruption have lower levels of earnings. Even after accounting for selectivity, the magnitude of this coefficient implies that those who have experienced an interruption due to caregiving earn 22 percent less than those never experiencing a caregiving interruption.[14]

For the remaining independent variables of the earnings equation, the intercept is positive, and the age and age-squared coefficients have the expected signs and magnitude, respectively, demonstrating the existence of the typical hump-shaped age-earnings profile. As indicated by the positive and increasing coefficients on the education dummy variables, and relative to those possessing less than a high-school education, each successive level of educational attainment on average translates into

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[13] If β is the estimated coefficient on a dummy variable X where the dependent variable is ln(Y), then the percentage difference in the predicted value of Y when X equals 1 versus when X equals 0 is equal to $100[\exp(\beta) - 1]$. Also, one would expect that the duration and timing (i.e., the length and whether recent or distant) of any particular interruption would play a role in predicting earnings. Unfortunately, our data does not allow us to determine the duration and timing of each individual interruption; we only have this information for caregiving interruptions (i.e., whether caring for a minor child, elderly family member, or disabled person). Given this data limitation, we are unable to account for individual interruption duration and timing in our model.

[14] The correlation coefficient, $\rho_{\varepsilon v}$, is significant, indicating that selection bias is evident in the data and should be taken into account in estimating our model.

higher earnings: 23 percent more for a high-school diploma, 38 percent more for some college education, 72 percent more for a bachelor's degree, and 115 percent more for an advanced degree. Married females on average earn 5 percent less than non-married females. Relative to those living in the Northeast region of the U.S., those living in the South and Midwest regions earn less on average (8 percent and 3 percent less, respectively), while those living in the West region earn more (7 percent) on average. Those possessing a managerial or professional occupation earn the most on average (85 percent more compared to those employed in the services occupations) while those employed in the services occupations earn the least on average. Not surprisingly, those employed part time would expect to have lower earnings (44 percent less) than those employed full-time and those employed in the private sector would expect to have higher earnings (12 percent higher) compared to those employed in non-private sector jobs.

Using equation (3), and as discussed above, the non-caregiver/caregiver earnings differential demonstrated in Tables 1 and 2 can be decomposed into three components: (1) a human capital or endowment component; (2) a labor market imperfections component; and (3) a selectivity component. The three components of equation (3) can be calculated by estimating equations (1) and (2) for both the non-caregiving and caregiving groups separately.

Columns (2) and (3) of Table 2 show the regression results for the non-caregiver and caregiver groups. As can be seen in column (2), the results for the non-caregiver group mirror the results of the pooled sample: all of the coefficient signs are the same and the magnitudes of the coefficients are very similar.

For the caregiver group (column (3) of Table 2), we find differences in the signs and magnitudes of the coefficients compared to the non-caregiver group results. First, relative to a person who does not possess a high school diploma, the returns to a high school diploma and an advanced college degree are both lower compared to the returns experienced by non-caregivers (9 percent versus 24 percent for a high school diploma and 85 percent versus 115 percent for an advanced degree).

Second, the return to working in the private sector is significantly higher for the caregiver group compared to the non-caregiver group. Caregivers on average earn 56 percent more for working in the private sector while non-caregivers earn on average 12 percent more.

Third, the coefficient signs and magnitudes of the geographic region variables differ between caregivers and non-caregivers. Relative to those living in the Northeast region of the U.S., caregivers living in the Midwest and South regions have higher earnings (12 percent and 24 percent, respectively) while non-caregivers have lower earnings (3 percent and 8 percent, respectively). Caregivers living in the West have lower earnings (6 percent) while non-caregivers earn more (8 percent).

Lastly, relative to those employed in the service occupations, caregivers experience higher returns for each occupation group compared to non-caregivers: caregivers can expect to earn 171 percent more for being employed in a managerial or professional occupation while non-caregivers can expect to earn 84 percent more; caregivers can expect to earn 49 percent more for being employed in a sales occupation while non-caregivers can expect to earn 40 percent more; and caregivers can expect to earn 127 percent more for being employed in some other occupation while non-caregivers can expect to earn 28 percent more.

Using the regression results from columns (2) and (3) of Table 2, we can now calculate the three decomposition components of equation (3). Table 3 shows the results of our decomposition analyses. Recall, our decomposition methodology shown in equation (3) assumes that the non-caregiver group is the non-discriminatory norm. The mean sample characteristics (i.e., the means of X_j from equation (1)) used in decomposing the earnings differential are shown in Appendix Table A1.

The decomposition results in Table 3 show that almost one-third of the earnings differential between non-caregivers and caregivers can be explained by differences in human capital or endowment factors, such as age, education, and marital status, and employment characteristics, such as part-time or full-time work status, occupation, and the presence of past work interruptions.

However, the unexplained portion (i.e., the portion attributable to labor market imperfections) of the decomposition dominates the earnings differential, which suggests that caregivers are facing labor markets that are more favorable to non-caregivers. In other words, if there were only labor market imperfections confronting caregivers, the earnings differential would be even larger than the observed differential.[15]

The reasons for this labor market flaw are not readily explainable given our data. Certainly, data on employer preferences, forgone opportunities for promotion or training, earnings prior to the caregiving interruption, change of occupation as a result of not being able to return to one's pre-caregiving occupation, the intensity of the caregiving spell

[15] The earnings differential would be 26 percent higher; 0.5189 log points versus 0.4102 log points.

(i.e., type of caregiving provided), etc. would aid in explaining the earnings differential, but we do not have data on such characteristics.

For example, the "gap" in the work careers of caregivers (that presumably would be evident on a resume or job application) could raise a "red-flag" (whether legitimate or not) with prospective employers in regard to potential reasons for the interruption in a career. Some employers may inquire as to the reason for the career interruption and be sympathetic, but others may very well reject the ex-caregiver out-of-hand for fear of the potential employee having to take time off again or the employer may perceive the work career gap as being indicative of a lack of reliability or dependability on the part of the potential employee.[16] For the year 2006, one study found that the cost to businesses to replace women caregivers who quit their jobs because of their caregiving responsibilities was $2.8 billion, while the costs associated with absenteeism, workday interruptions, and unpaid leave were $4.0 billion, $3.3 billion, and $1.4 billion, respectively (MetLife Mature Market Institute and National Alliance of Caregiving, 2006). For female and male caregivers together, the same study found that the cost to businesses associated with caregivers reducing hours worked from full time to part time was $4.7 billion (MetLife Mature Market Institute and National Alliance of Caregiving, 2006). Consequently, by employers demonstrating a preference for non-caregivers, employers may be partly

[16] In May 2007, the federal Equal Employment Opportunity Commission (EEOC) issued its first guidance for employers on the disparate treatment of workers with caregiving responsibilities (EEOC Notice Number 915.002). Although the federal Equal Employment Opportunity laws do not prohibit discrimination against caregivers per se, there are circumstances in which discrimination against caregivers might constitute unlawful disparate treatment. The purpose of the EEOC guidance is to assist investigators, employees, and employers in assessing whether a particular employment decision affecting a caregiver is prohibited under current laws. One organization, The Work Life Law Center at the University of California Hastings College of the Law, compiles case statistics concerning family responsibilities discrimination. See http://www.worklifelaw.org for more information.

reacting to the possibility of incurring future costs related to productivity losses from absenteeism, workday interruptions, and unpaid leave if they hire past caregivers.

Another possible source of the unexplained portion of the earnings differential could lie in the fact that those having to interrupt their work career for caregiving were passed-over for promotions, advancement opportunities, or forced to transition to a new field of work due to being away from their job. These missed opportunities could limit their future earnings potential when they return from their caregiving interruption, and if they do not return to their pre-caregiving employer, may hamper their ability to attain the same level of responsibility and pay with another employer.[17] One national study on women and caregiving found that among women who continued to work while providing care, 29 percent passed up a job promotion, training, or other assignment due to having to provide care (MetLife Mature Market Institute, et al., 1999). Presumably, those who took leaves of absence or quit their jobs entirely to provide care also missed opportunities for promotion, training, or other advancement opportunities. Furthermore, if the caregiver were unable to return to their pre-caregiving occupation after their work interruption, they would have to transition to a new field of work. Given that transitioning to a new occupation typically entails taking an entry-level position (and most likely at entry level wages), this would result in lower earnings levels for this subset of caregivers.[18]

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[17] Pavalko and Artis (1997) find that even when a woman's caregiving duties ended, they did not increase their hours worked, suggesting difficulty with recouping the employment losses associated with their time out of the workforce.

[18] Clearly, to more adequately address the role of post-caregiving occupation in explaining the earnings differential, one would not only need information concerning one's post-caregiving occupation (which we have) but also information concerning one's pre-caregiving occupation. Likewise, one's earnings level prior to the caregiving interruption could also play a role in explaining the earnings differential. For example, it could be the case that those women who choose to provide care have lower earnings prior to the caregiving interruption; hence, they choose to provide care as the opportunity cost of stopping work is relatively low. Unfortunately, these types of before and after analyses are not available to us given our data.

Returning to our decomposition results in Table 3, the portion of the earnings differential attributable to selectivity differences indicates that differences in how non-caregivers and caregivers select into the labor market favor caregivers. Recall, this effect is caused by differences in unobserved characteristics and the returns to these characteristics. For example, differences in unobserved characteristics, such as ability and motivation, indicate that caregivers have an advantage over non-caregivers and this advantage reduces the earnings differential by -0.2313 log points. One could hypothesize that higher returns to such characteristics for caregivers are linked to the choice of whether or not to stop working to become a caregiver. Deciding to stop working entirely to become a caregiver is not an easy decision to make, particularly when knowing that deciding to become a caregiver will entail the devotion of a significant amount of time and energy to the caregiving duties, while at the same time still having to address other family responsibilities. Taking on such a challenge would require motivation and other talents such as organizational and time management skills. Certainly, some of this increased "energy" would translate into higher returns in the labor market when the caregiver returns to the labor market and could partially explain why we find selectivity differences favoring caregivers.

Lastly, and in regard to the overall earnings differential, the level of caregiving intensity (i.e., providing care for a terminally ill or severely, mobility-limited family member versus a family member that only needs help with groceries or small chores) would presumably have a differential impact on the labor market outcomes of caregivers. The more intense the level of caregiving, the more likely an individual will have to take a leave of absence from their job to provide care. If the majority of our caregiver sample were primarily composed of high intensity caregivers, then our observed earnings differential could be interpreted as an upper limit estimate. Unfortunately, our data does not provide information on the type of care provided; however, one can argue that since we are examining caregivers who interrupted their work careers by stopping work entirely, we are more likely to be examining the impact of high-intensity caregiving duties on labor market earnings.

V. CONCLUSION

In this paper, we analyze and decompose the earnings differential observed between females who have interrupted their work careers to care for an elderly family member (i.e., caregivers) and those females who have never had such a work interruption (i.e., non-caregivers). The purpose of this paper was to gain a better understanding of the non-caregiver/caregiver earnings differential observed in the data by estimating a straightforward model of earnings to determine the extent to which human capital and selectivity differences play a role in explaining the earnings differential. Our data come from the 2004 panel of the Survey of Income and Program Participation (SIPP), in particular the wave one core and Employment History topical module data.

Our data show those females currently employed and who have experienced a caregiving interruption over their work career earn on average 25 percent less than currently employed females who have never had a caregiving work interruption, and females who have experienced a caregiving interruption were more likely to have experienced multiple work interruptions (i.e., two or more) over their work career. Our data show on average, those females who have had a work interruption due to caregiving for an older family member were five years older, less likely to be Hispanic, less likely to possess a four-year college or advanced degree, less likely to be married, more likely to live in the southern region of the country, and less likely to be currently employed. Furthermore, for those females currently employed and who have experienced a caregiving interruption over their work career, they were more likely to be part-time workers (i.e., work less than 35 hours per week), and less likely to be employed in a management or professional occupation.

In order to examine the observed earnings differential between female caregivers and non-caregivers, we jointly estimate the labor market participation decision and log-earnings functions for female caregivers and non-caregivers while accounting for selectivity bias. We use the outcomes from this simultaneous estimation as the basis for our Blinder-Oaxaca decomposition analysis.

The decomposition results reveal that about one-third of the caregiver/non-caregiver earnings differential is attributable to human capital or endowment differences, such as age, education, and marital status, and employment characteristics, such as part-time or full-time work status, occupation, and the presence of past work interruptions. The remaining portion (i.e., the unexplainable portion) is attributable to labor market imperfections and lack of data on other variables that may or may not affect the earnings of caregivers and non-caregivers.

We hypothesize as to the possible sources of this unexplainable portion of the earnings differential and that data on employer preferences, forgone opportunities for promotion or training, earnings prior to the caregiving interruption, change of occupation as a result of not being able to return to one's pre-caregiving occupation, and the intensity of the caregiving spell (i.e., type of caregiving provided) would aid in explaining the earnings differential; however, we do not have data on such characteristics. Regardless, we consider the existence of the sizeable unexplained portion as partial evidence of the presence of these anecdotal scenarios.

Lastly, we find strong evidence of selection differences between the caregiver and non-caregiver groups. Our data show that caregivers have an advantage over non-caregivers in regard to the returns on these unobserved characteristics, such as ability and motivation.

In future research, and by further exploiting the available data from the SIPP Employment History topical module used in this paper, we plan to extend our basic model by explicitly incorporating a calculated work experience variable in place of our age terms and whether an individual had an earlier work interruption due to providing care for a child. Also, we plan to account for household composition via an indicator for the presence of young children in the household and for an individual's current job tenure. With these additional covariates, we anticipate that the portion of the earnings differential that we are able to explain will rise, though we still anticipate the unexplainable portion to remain sizeable.

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Table 1. Sample Characteristics of Female Non-Caregivers and Caregivers 25 to 62 Years of Age

Characteristic	All n = 72,949,637	Non-Caregivers n = 71,969,307	Caregivers n = 960,330
Mean monthly earnings[1] (2004 dollars)	$2,796	$2,802	$2,112
	($27.03)	($27.24)	($172.37)
Mutiple work interruptions (percent)	17.3	16.9	44.7
	(0.30)	(0.30)	(3.35)
Mean Age (years)	42.8	42.8	47.9
	(0.08)	(0.08)	(0.61)
Race and Ethnicity (percent)			
Black[2]	12.9	12.9	15.5
	(0.27)	(0.27)	(2.44)
Hispanic	12.4	12.5	7.5
	(0.26)	(0.26)	(1.78)
Educational Attainment (percent)			
Less than High-school diploma	11.1	11.1	13.4
	(0.25)	(0.25)	(2.30)
High-school diploma	24.0	24.0	20.7
	(0.34)	(0.34)	(2.73)
Some college	36.7	36.6	45.6
	(0.38)	(0.39)	(3.36)
Bachelor's degree	18.9	19.0	16.1
	(0.31)	(0.31)	(2.48)
Advanced degree	9.3	9.3	4.1
	(0.23)	(0.23)	(1.33)
Married (percent)	63.8	63.9	55.3
	(0.38)	(0.38)	(3.35)
Region (percent)			
Northeast	19.2	19.2	17.1
	(0.31)	(0.32)	(2.54)
South	35.8	35.7	42.1
	(0.38)	(0.38)	(3.33)
Midwest	22.0	22.0	17.1
	(0.33)	(0.33)	(2.54)
West	23.0	23.0	23.6
	(0.33)	(0.34)	(2.86)
Employment (percent)			
Employed	70.7	70.9	52.5
	(0.36)	(0.36)	(3.37)
Part-time[1]	36.2	36.0	51.3
	(0.46)	(0.46)	(4.67)
Private sector[1]	71.9	71.9	71.7
	(0.43)	(0.43)	(4.21)
Occupation Group[1] (percent)			
Management and professional	41.3	41.3	32.9
	(0.47)	(0.47)	(4.39)
Service	17.7	17.6	23.7
	(0.36)	(0.36)	(3.97)
Sales and office	33.1	33.1	31.1
	(0.45)	(0.45)	(4.33)
Other	8.0	7.9	12.3
	(0.26)	(0.26)	(3.07)

[1] For those females employed in wave one.

[2] Federal surveys now give respondents the option of reporting more than one race. There are two basic ways of defining a race group. A group such as Black may be defined as those who reported Black and no other race (the race-alone or single-race concept) or as those who reported Black regardless of whether they also reported another race (the race-alone-or-in-combination concept). This table shows data using the first approach (race alone). The use of the single-race population does not imply that it is the preferred method of presenting or analyzing data. The Census Bureau uses a variety of approaches. Information on people who reported more than one race, such as White and American Indian and Alaska Native, or Asian and Black or African American, is available from Census 2000 through the American FactFinder®. About 2.6 percent of people reported more than one race in Census 2000.

Note: All estimates are weighted and standard errors are in parentheses. All standard errors have been adjusted for the complex sample design of the SIPP by the use of a design effect factor. Specifically, the square root of the design effect factor of 1.80 (i.e., 1.34) was applied to all SAS standard errors. For more information, see U.S. Census Bureau (2007).

Unweighted counts: Non-caregivers: 27,923; Caregivers: 397.

Source: Survey of Income and Program Participation, Wave one core and Employment History topical module data, 2004 Panel.

Table 2. Regression Results for Females 25 to 62 Years of Age

Earnings Equation[1]:

Independent Variable	(1) All n = 51,559,325 Coefficient		(2) Non-Caregivers n = 51,055,271 Coefficient		(3) Caregivers n = 504,054 Coefficient	
Constant	6.0958	***	6.1105	***	2.9774	***
	(0.0034)		(0.0034)		(0.0467)	
Age	0.0412	***	0.0407	***	0.1476	***
	(0.0001)		(0.0001)		(0.0020)	
Age-squared	-0.0004	***	-0.0004	***	-0.0016	***
	(0.0000)		(0.0000)		(0.0000)	
Black	0.0013	***	0.0016	***	-0.1241	***
	(0.0004)		(0.0004)		(0.0059)	
Hispanic	-0.0946	***	-0.0925	***	-0.5384	***
	(0.0005)		(0.0005)		(0.0088)	
High-school	0.2113	***	0.2120	***	0.0829	***
	(0.0007)		(0.0007)		(0.0103)	
Some College	0.3204	***	0.3208	***	0.3684	***
	(0.0008)		(0.0008)		(0.0101)	
Bachelor's Degree	0.5444	***	0.5449	***	0.5396	***
	(0.0009)		(0.0009)		(0.0117)	
Advanced Degree	0.7650	***	0.7674	***	0.6138	***
	(0.0010)		(0.0010)		(0.0146)	
Married	-0.0528	***	-0.0530	***	-0.0638	***
	(0.0003)		(0.0003)		(0.0043)	
Part-time	-0.5903	***	-0.5878	***	-0.7819	***
	(0.0003)		(0.0003)		(0.0040)	
Private Sector	0.1181	***	0.1157	***	0.4484	***
	(0.0003)		(0.0003)		(0.0047)	
Midwest Region	-0.0279	***	-0.0283	***	0.1146	***
	(0.0004)		(0.0004)		(0.0067)	
West Region	0.0712	***	0.0744	***	-0.0644	***
	(0.0004)		(0.0004)		(0.0062)	
South Region	-0.0803	***	-0.0817	***	0.2161	***
	(0.0004)		(0.0004)		(0.0057)	
Management and Professional Occupations	0.6159	***	0.6115	***	0.9989	***
	(0.0004)		(0.0004)		(0.0058)	
Sales and Office Occupations	0.3397	***	0.3383	***	0.3986	***
	(0.0004)		(0.0004)		(0.0053)	
Other Occupations	0.2530	***	0.2467	***	0.8187	***
	(0.0006)		(0.0006)		(0.0067)	
Multiple Interruptions	-0.1367	***	-0.1391	***	-0.0557	***
	(0.0004)		(0.0004)		(0.0039)	
Caregiving	-0.2503	***	---		---	
	(0.0014)		---		---	
Sigma (σ_ε)	0.7495	***	0.7461	***	1.0101	***
	(0.0001)		(0.0001)		(0.0022)	
Rho ($\rho_{\varepsilon v}$)	0.0601	***	0.0569	***	0.3710	***
	(0.0016)		(0.0016)		(0.0071)	

Note: All estimates are weighted and standard errors are in parentheses. All standard errors have been adjusted for the complex sample design of the SIPP by the use of a design effect factor. Specifically, the square root of the design effect factor of 1.80 (i.e., 1.34) was applied to all SAS standard errors. For more information, see U.S. Census Bureau (2007).

[1] The dependent variable is the natural log of monthly earnings.

*** Indicates the coefficient is significant at the one percent level.

Unweighted counts: Non-caregivers: 19,741; Caregivers: 207.

Source: Survey of Income and Program Participation, Wave one core and Employment History topical module data, 2004 Panel.

Table 2. Regression Results for Females 25 to 62 Years of Age (continued)

Participation Equation[1]:

Independent Variable	(1) All n = 72,949,637 Coefficient		(2) Non-Caregivers n = 71,969,307 Coefficient		(3) Caregivers n = 960,330 Coefficient	
Constant	-1.9157 (0.0038)	***	-1.9146 (0.0038)	***	-2.6628 (0.0414)	***
Age	0.1060 (0.0002)	***	0.1061 (0.0002)	***	0.1237 (0.0018)	***
Age-squared	-0.0013 (0.0000)	***	-0.0013 (0.0000)	***	-0.0017 (0.0000)	***
Black	-0.0275 (0.0007)	***	-0.0288 (0.0007)	***	0.0628 (0.0054)	***
Hispanic	-0.0674 (0.0007)	***	-0.0702 (0.0007)	***	-0.0427 (0.0074)	***
High-school	0.5285 (0.0007)	***	0.5233 (0.0008)	***	0.7785 (0.0067)	***
Some College	0.7356 (0.0007)	***	0.7352 (0.0007)	***	0.8743 (0.0061)	***
Bachelor's Degree	0.8998 (0.0008)	***	0.8940 (0.0008)	***	1.3679 (0.0074)	***
Advanced Degree	1.1430 (0.0010)	***	1.1323 (0.0010)	***	1.9002 (0.0123)	***
Married	-0.2304 (0.0005)	***	-0.2338 (0.0005)	***	-0.1695 (0.0039)	***
Midwest Region	0.0918 (0.0007)	***	0.0918 (0.0007)	***	0.0695 (0.0062)	***
West Region	-0.0055 (0.0007)	***	-0.0073 (0.0007)	***	0.1796 (0.0060)	***
South Region	0.0086 (0.0006)	***	0.0123 (0.0006)	***	-0.1122 (0.0054)	***

Note: All estimates are weighted and standard errors are in parentheses. All standard errors have been adjusted for the complex sample design of the SIPP by the use of a design effect factor. Specifically, the square root of the design effect factor of 1.80 (i.e., 1.34) was applied to all SAS standard errors. For more information, see U.S. Census Bureau (2007).

[1] The dependent variable is equal to one for employed and zero otherwise.

*** Indicates the coefficient is significant at the one percent level.

Unweighted counts: Non-caregivers: 27,923; Caregivers: 397.

Source: Survey of Income and Program Participation, Wave one core and Employment History topical module data, 2004 Panel.

Table 3. Decomposition of Earnings Differential Between Female Non-Caregivers and Caregivers

	Contribution Due to		
Earnings Differential (log points)	**Human Capital Differences** (log points/as percentage)	**Labor Market Imperfection Differences** (log points/as percentage)	**Selectivity Differences** (log points/as percentage)
0.4102	0.1226 29.89%	0.5189 126.50%	-0.2313 -56.39%

Source: Survey of Income and Program Participation, Wave one core and Employment History topical module data, 2004 Panel.

Appendix Table A1. Mean Sample Characteristics Used in Decomposing the Monthly Earnings Differential[1]

Independent Variable	Non-Caregivers n = 51,055,271	Caregivers n = 504,054
Natural Log of Monthly Earnings	7.6070 (1.1943)	7.1968 (1.5837)
Multiple Interruptions	16.6 (0.35)	50.7 (4.67)
Age	42.3 (0.09)	46.4 (0.83)
Age-squared	1886.5 (8.16)	2227.8 (73.61)
Black	13.0 (0.32)	16.0 (3.43)
Hispanic	10.7 (0.29)	5.7 (2.16)
High-school	22.4 (0.40)	18.8 (3.65)
Some College	38.3 (0.46)	47.2 (4.67)
Bachelor's Degree	21.1 (0.39)	21.4 (3.84)
Advanced Degree	11.2 (0.30)	6.7 (2.33)
Married	62.1 (0.46)	51.5 (4.67)
Part-time	36.0 (0.46)	51.4 (4.67)
Private Sector	71.9 (0.43)	71.7 (4.21)
Midwest Region	22.9 (0.40)	17.1 (3.52)
West Region	22.5 (0.40)	26.6 (4.13)
South Region	35.3 (0.46)	38.7 (4.55)
Management and Professional Occupations	41.3 (0.47)	32.9 (4.39)
Sales and Office Occupations	33.1 (0.45)	31.1 (4.33)
Other Occupations	7.9 (0.26)	12.3 (3.07)

Note: All estimates are weighted and standard errors are in parentheses. All standard errors have been adjusted for the complex sample design of the SIPP by the use of a design effect factor. Specifically, the square root of the design effect factor of 1.80 (i.e., 1.34) was applied to all SAS standard errors. For more information, see U.S. Census Bureau (2007).

[1] The mean sample characteristics shown are only for those with positive monthly earnings.

Unweighted counts: Non-caregivers: 19,741; Caregivers: 207.

Source: Survey of Income and Program Participation, Wave one core and Employment History topical module data, 2004 Panel.